Arabian Journal of Geosciences (2023) 16:488
https://doi.org/10.1007/s12517-023-11561-4

ORIGINAL PAPER

Application of artificial intelligence techniques for predicting the flyrock, Sungun mine, Iran

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Received: 4 May 2022 / Accepted: 17 June 2023 / Published online: 24 July 2023

Abstract
Flyrock is known as one of the main problems in open pit mining operations. This phenomenon can threaten the safety of mine personnel, equipment and buildings around the mine area. One way to reduce the risk of accidents due to flyrock is to accurately predict that the safe area can be identified and also with proper design of the explosion pattern, the amount of flyrock can be greatly reduced. For this purpose, 14 effective parameters on flyrock have been selected in this paper i.e. burden, blasthole diameter, sub-drilling, number of blastholes, spacing, total length, amount of explosives and a number of other effective parameters, predicting the amount of flyrock in a case study, Songun mine, using linear multivariate regression (LMR) and artificial intelligence algorithms such as Gray Wolf Optimization algorithm (GWO), Moth-Flame Optimization algorithm (MFO), Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO) and Multi-Verse Optimizer (MVO). Results showed that intelligent algorithms have better capabilities than linear regression method and finally method MVO showed the best performance for predicting flyrock. Moreover, the results of the sensitivity analysis show that the burden, ANFO, total rock blasted, total length and blast hole diameter are the most significant factors to determine flyrock, respectively, while dynamite has the lowest impact on flyrock generation.

Keywords Flyrock · Blasting · LMR · GWO · MFO · WOA · ALO · MVO · sensitivity analysis

Introduction

It is well known that in mining and construction projects in the face of changing conditions of rock mass and hard rocks, due to economic conditions and flexibility of the type of drilling operations is of great importance. Today, despite the advances made in the construction of stone cutting and drilling machines, blasting is still the main solution for mineral extraction and rock fragmentation in mining and construction projects (Shakeri et al. 2020; Bui et al. 2020; Monjezi et al. 2021; Murlidhar et al. 2020; Shang et al. 2019). Among the favorable results of accurate and optimal blasting operations, we can mention the reduction of costs and the improvement of efficiency in drilling operations. Studies have shown that all of the energy is not used for fragmentation; instead, a large portion of this energy, about 70%, is wasted due to adverse and harmful phenomena caused by the explosion, such as ground vibration, flyrock and back-firing air vibration (Shakeri et al. 2020; Fouladgar et al. 2017; Monjezi et al. 2021; Nguyen et al. 2021; Nguyen et al. 2020; Nguyen et al. 2019a; Nguyen et al. 2019b; Yang et al. 2020).

Flyrock is a relevant environmental issue, which is created when the energy released by an explosion travels the shortest path of resistance. This event can pose an earnest menace to construction adjacent to the site and personnel working nearby. Therefore, accurate fly rock estimation is very important to minimize these problems (Trivedi et al. 2015; Hasanipanah et al. 2020; Little and Blair 2010; Hajihassani et al. 2015; Koopialipoor et al. 2019). Flyrock divisions include face bursting, rifling, and cratering. (see Figure 1).

Based on previous research, controllable and uncontrollable parameters can be considered as the most important

Highlights
• The accuracy of the more than 5 AI techniques are compared.
• Sensitivity analysis has been done for finding the most effective parameters on flyrock.
• The results are compared with a real case.

Responsible Editor: Murat Karakus

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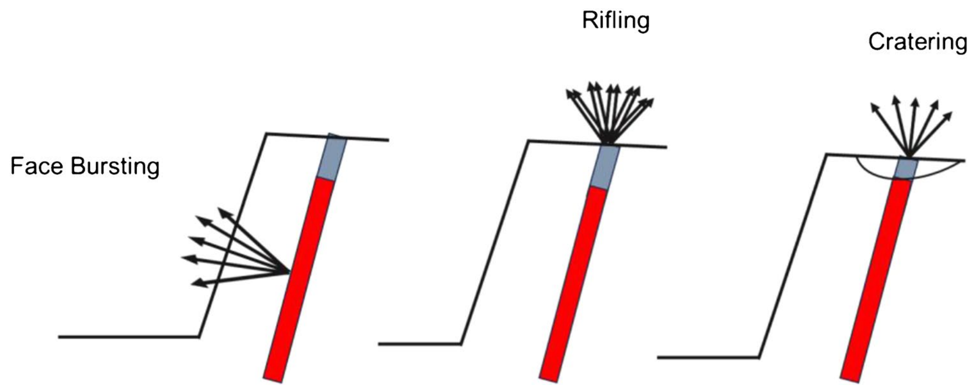


Fig. 1 Flyrock phenomenon categories (Zhou et al. 2020a; Richards and Moore 2004)

factors affecting flyrock. (Rehak et al. 2001; Monjezi et al. 2012 & Monjezi et al. 2013; Hasanipanah et al. 2017; Ghasemi et al. 2014). Controllable parameters include powder factor, burden, hole spacing, height stemming, hole length, hole diameter, sub-drilling, and so forth. Besides, uncontrollable parameters include natural cavities, rock mass characteristics and non-resistant features, including bedding planes, faults, and joints (Rad et al. 2018, 2020; Persson et al. 2018; Bajpayee et al. 2004). For many years, the importance of investigating flyrock caused by explosions in mines and construction projects has led many researchers to conduct extensive studies to predict and evaluate the rate of flyrock caused by explosions.

Monjezi et al. 2021, used methods LMR and GEP to predict flyrock. The parameters of powder factor, length of stemming, burden and hole spacing were considered as input and flyrock as output. The results of their studies show better performance of GEP model in fly rock prediction than LMR model. Murlidhar et al. 2021 investigated and estimated flyrock distance due to explosion using five artificial intelligent algorithms (MLP, RF, SVM and Combining Harris Hawks model based on MLP (HHO-MLP)). To conduct their research, they used the results of 152 explosions in Malaysia. The measured data included blast parameters and rock mass properties. The results of their studies show that HHO-MLP performed best among all models. Bhagat et al. 2021, have tried to use the CART method (tree classification and regression) to predict flyrock. They compared the results of LMR method with CART, which used two statistical indices, R^2 and RSME, to evaluate the results of the models. Their results show that the CART model offers better output than the MLR model. Kalaivaani et al. 2020, used the combination of RFNN with PSO algorithm to predict flyrcok due to explosion in mines. ANFIS and MLR were also used to evaluate the acceptability of the RFNN-PSO method. Their results indicate the accuracy of the RFNN-PSO method in predicting flyrock. Dehghani et al. 2021 used GEP and cuckoo algorithms (COA) to predict fly rock due to an explosion at the Songun copper mine. They obtained the predictive equation of an explosion-induced flyrock using GEP. The equation obtained from GEP is then used as a cost function to minimize flyrock by the COA. The results of their studies show the appropriate accuracy of GEP in predicting fly rock. In addition, there was a 43.6% reduction in the maximum amount of explosion-proof flyrock provided by the COA compared to the maximum amount in the original blast designs. Shakeri et al. 2022a, explored different prediction methods and identified the ANN model as the optimal approach for predicting flyrock, achieving notable accuracy. Additionally, they highlighted the effectiveness of the ICA technique and emphasized the importance of powder factor and blasthole diameters in determining flyrock distance.

So far, plenty of reviews have been conducted to estimate the distance of fly-rock based on artificial intelligence techniques, the effectiveness of which varies. In addition, depending on the geological conditions, the location of each mine and the design parameters of the explosion, it can be said that the fly-rock distance and its effects are different. Based on the mentioned points, the present study is conducted with the aim of using statistical and intelligent methods to evaluate the amount of flyrock caused by the explosion in the Songun mine.

Methods

Linear multivariate Regression Model (LMR)

In 1908, Pearson used regression analysis to determine the contribution of independent variables in predicting the dependent variable. In regression analysis, the aim is to predict the changes of the dependent variable with respect to the changes of the independent variables. Using multivariate regression, the researcher can study the linear relationship between a set of independent variables with a dependent variable in a way that the existing relationships between independent variables are also considered (Monjezi et al. 2021; Shakeri et al. 2020; Onyelowe and Shakeri 2021; Jodeiri Shokri et al. 2020). Multivariate regression analysis is quite suitable for studying the effects of independent multivariate on a dependent variable. Hence, for many years, many researchers have used this method to solve statistical issues in important fields of engineering, including mining and civil engineering. (Moomivand et al. 2022; Monjezi et al. 2021; Onyelowe et al. 2022; Armaghani et al. 2016; Onyelowe et al. 2021b). The following is a typical multiple regression formula:

$$C = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \tag{1}$$

where: ε: error; $j = 0, 1, \ldots, n$ and β_j are the regression coefficients (Barbur et al. 1994; Monjezi et al. 2021; Shakeri et al. 2020; Armaghani et al. 2016; Onyelowe and Shakeri 2021; Onyelowe et al. 2021a; Jodeiri Shokri et al. 2020).

Gray Wolf Optimization algorithm (GWO)

GWO was proposed by Mirjalili et al. 2014. This algorithm belongs to a class of swarm-based meta-heuristic algorithms inspired by the natural life and unique behavior of gray wolves in hunting (Mirjalili et al. 2014). GWO can be used to solve complex optimization issues in engineering (Yu et al. 2020; Xu et al. 2020; Choopan and Emami 2019). Gray wolves are classified as Canidae and have extremely precise class hierarchies that is divided into four groups based on their abilities (see figure 2), including alpha (α), beta (β), delta (δ) and omega (ω) wolves (Purushothaman et al. 2020; Emary et al. 2017; Mirjalili et al. 2014; Emami et al. 2018; Goli et al. 2019; Onyelowe et al. 2022).

The wolf alpha (α) makes decisions including hunting and sleeping as the group leader. And the next group that helps the α group make decisions are the obedient wolves or the wolf beta (β) commanders. The wolf β is known as the second largest wolf in the group and is likely to become a leader (α). Subordinates of delta wolves (δ) and lowest-ranking omega wolves (ω) are those who perceive safety and ensure the competence of wolf herds. According to studies, GWO uses the process of siege, hunting, attack and recovery to hunt prey (Mirjalili et al. 2014; Dehghanbanadaki et al. 2021; Purushothaman et al. 2020). The process of the GWO algorithm is shown in Figure 3 and is repeated until it reaches the stop criterion. The exact formula for GWO is described in the literature (Mirjalili et al. 2014; Lawal et al. 2021a; Xu et al. 2020; Onyelowe et al. 2022; Yu et al. 2020; Emary et al. 2017; Goli et al. 2019; Purushothaman et al. 2020).

Moth-Flame Optimization algorithm (MFO)

One of the optimization algorithms is MFO proposed by Mirjalili (2015a). MFO is inspired by biology in nature, which is based on the process of transverse orientation of butterflies in reality. In MFO, mothes are always looking to maintain a constant angle to the moon to fly, and when artificial light is emitted, the butterflies try to keep the same direction with that light after flying so that they can fly in a straight line. According to what has been said, Figure 4 shows the transverse direction with respect to the farther light by the moth and its spiral motion around the near artificial light (Lawal et al. 2021b; Bui et al. 2021; Onyelowe et al. 2022; Mirjalili 2015b; Barham et al. 2018). According to Lin et al. 2020, the trend of spiral flight by butterflies includes that in the search space of the spiral flight space of the butterfly, the spiral butterfly flight is the starting point and the end point of the spiral flight ends in the flame position.

According to Figure 5, which shows the MFO trend, first, a population of mothes is randomly generated and their suitability values are calculated. Then, in the iteration step, the main function is performed and the butterflies are moved in the search space. After that, if the criterion of stopping is observed, it returns correctly; Otherwise, an incorrect item will be returned (Lawal et al. 2021a; Bui et al. 2021; Mirjalili 2015a; Barham et al. 2018; Onyelowe et al. 2022). Flight mode simulation and positioning of each butterfly are expressed by Equation (2):

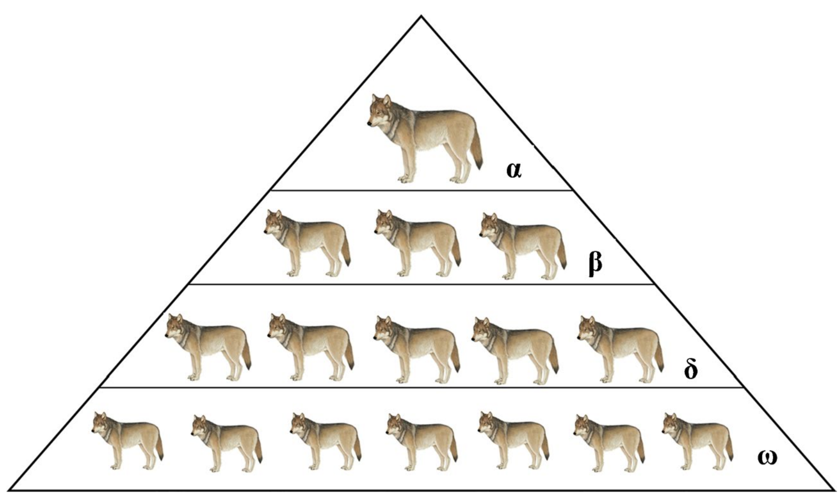


Fig. 2 Classify wolves based on their abilities (Mirjalili et al. 2014)

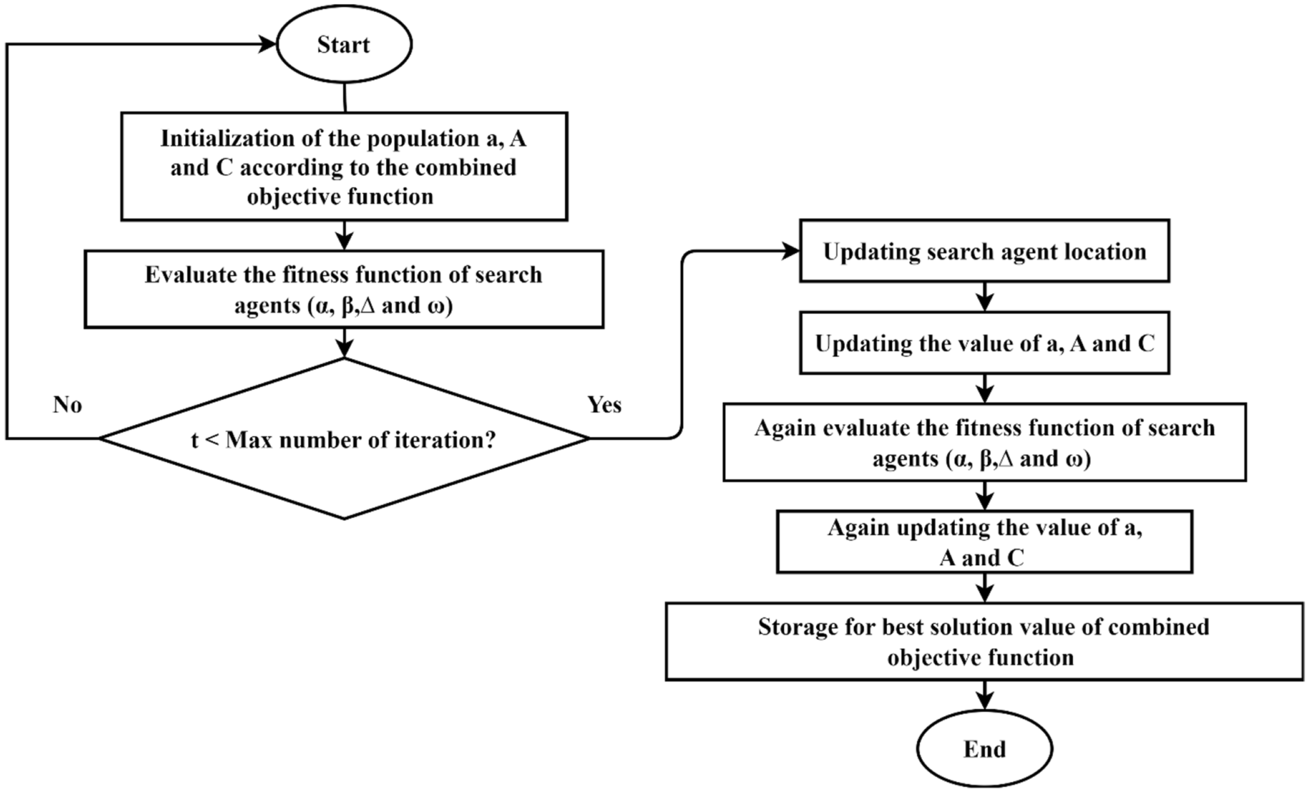


Fig. 3 GWO flowchart (Chawla et al. 2019)

$$M_i = D_i . e^{bt} . \cos(2\pi t) + F_j \quad (2)$$

where t is a random number between [-1, 1], Di refers to the space between the i-th moth and the j-th flame (D_i=G_i-M_i), b is a constant for defining the logarithmic helix shape, and. In Mirjalili (2015b), a detailed description of the MFO can be found.

Whale Optimization Algorithm (WOA)

Mirjalili and Lewis (2016) have proposed the Whale Optimization Algorithm (WOA), which falls into the category of new random optimization algorithms. WOA is inspired by the behavior of humpback whales. These whales use a bubble hunting strategy to hunt their prey. According to figure 6, the humpback whale dives about 10-15 meters into the water to catch its prey, and after starting to produce bubbles in the form of a spiral, it covers the prey and then follows the bubbles upwards (Mirjalili and Lewis 2016; Youcefi et al. 2020; Memarzadeh et al. 2020; Louis et al. 2019). WOA has positive features that include:

- WOA has been improved based on easy concepts in order to be able to easily implement and apply WOA in various applications.
- WOA has several adjustment parameters that can be simply adjusted for several applications.
- WOA has the ability to escape the optimal local response. Therefore, WOA can find the optimal universal respond.
- Eventually, WOA can address different problems through various trends (Mirjalili and Lewis 2016; Louis et al. 2019).

WOA has been tested with 29 mathematical optimization problems and 6 structural design issues, which can be seen in Mirjalili and Lewis (2016). Exploration and exploitation

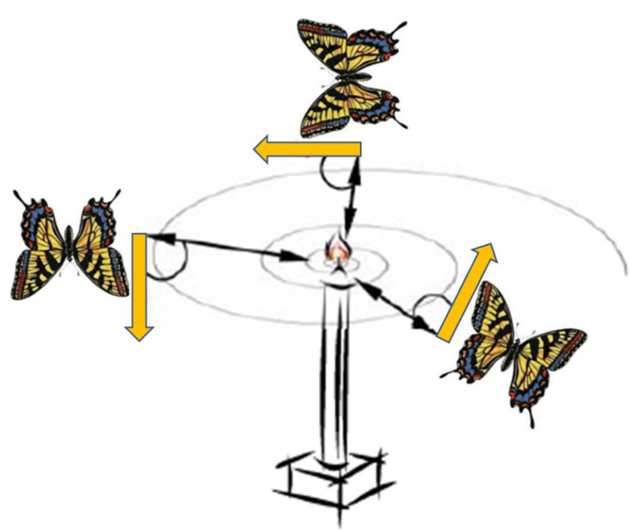


Fig. 4 Moth movement around artificial light source (Mirjalili 2015a)

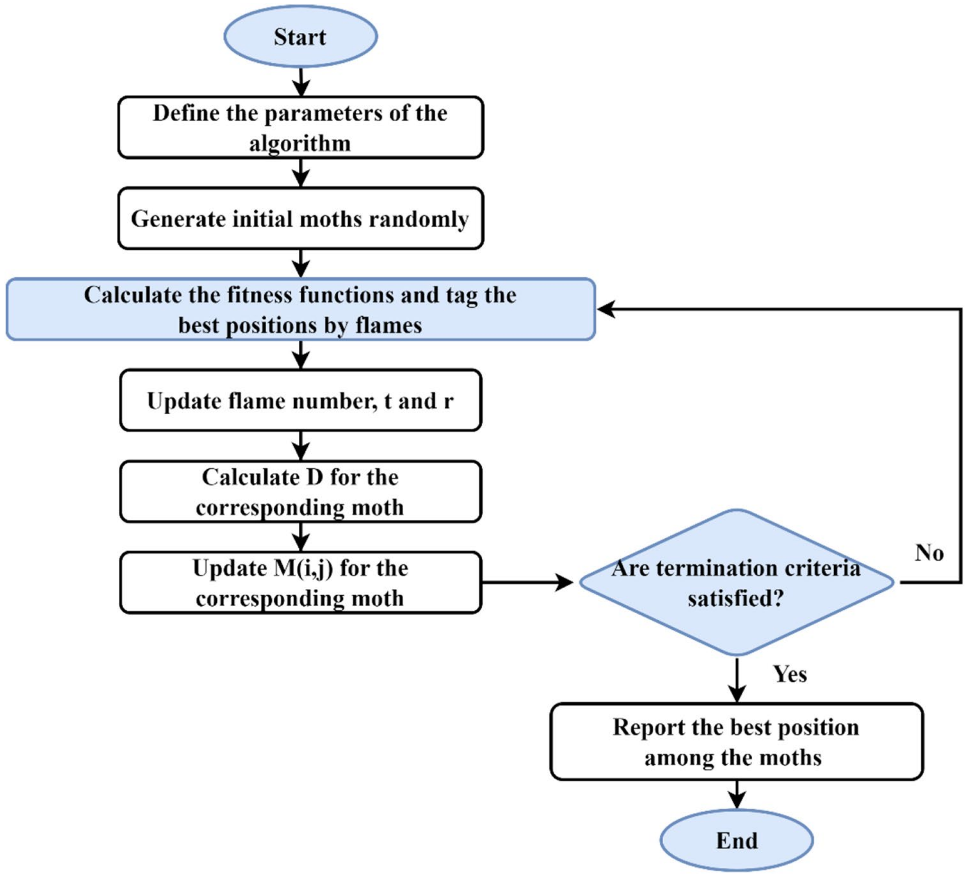


Fig. 5 MFO flowchart Mirjalili (2015a)

are the two main stages in whale search behavior. According to the general WOA trend shown in Figure 7, first, the optimal global approximation begins with the WOA starting the whale population in a random position. Then, at this stage, called the exploration stage, whales begin a random search in their surroundings to find prey. Once the whales have found their prey, they identify the situation and begin to encircle them during the exploitation phase with the bubble feeding method. After determining the whale with the best fitness, the whale's best situation to search for prey to other whales is updated. Finally, the other whales move to the situation of the whale with the best fitness by updating their situation (Mirjalili and Lewis 2016; Youcefi et al. 2020; Memarzadeh et al. 2020; Louis et al. 2019).

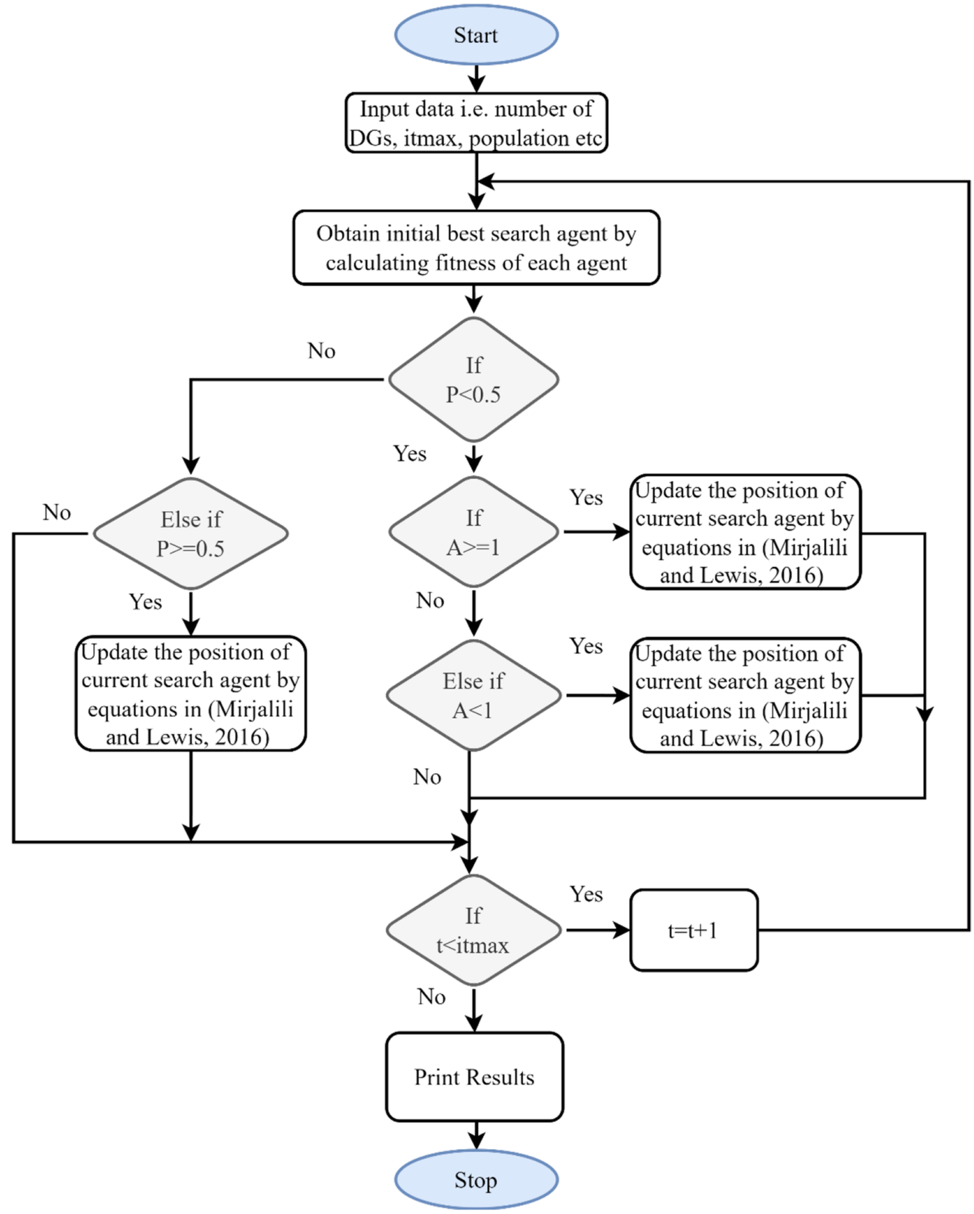
Ant Lion Optimizer (ALO)

ALO, which is based on the behavior of ants in the natural environment, was introduced by Mirjalili 2015b. ALO has five main stages that include random walk of ants, constructing traps, entrapment of ants in traps built by antlions, catching ants, and re-setup the traps for re-hunting. The antlions belong to the family Myrmeleontidae and the order Neuroptera. The life cycle of antlions consists of two stages, larvae and adults. Their entire normal life lasts up to 3 years, which occurs mostly in larvae. They hunt at the larvae stage and reproduce at puberty.

A view of the typical antlion traps and traps is provided in Figure 8. An antlion larva digs a conical insole in the sand by moving along a circular path. After that, he uses it to throw sand out of his huge jaws. Then, they hide at the end of the cone and wait for the insects to be trapped and hunted. When a prey is caught in a trap, the antlion senses it and starts to catch it. At the same time, insects usually do not get caught

Fig 6 Production of bubbles for hunting by humpback whales (Mirjalili and Lewis 2016)

Fig. 7 Flowchart of whale optimization algorithm



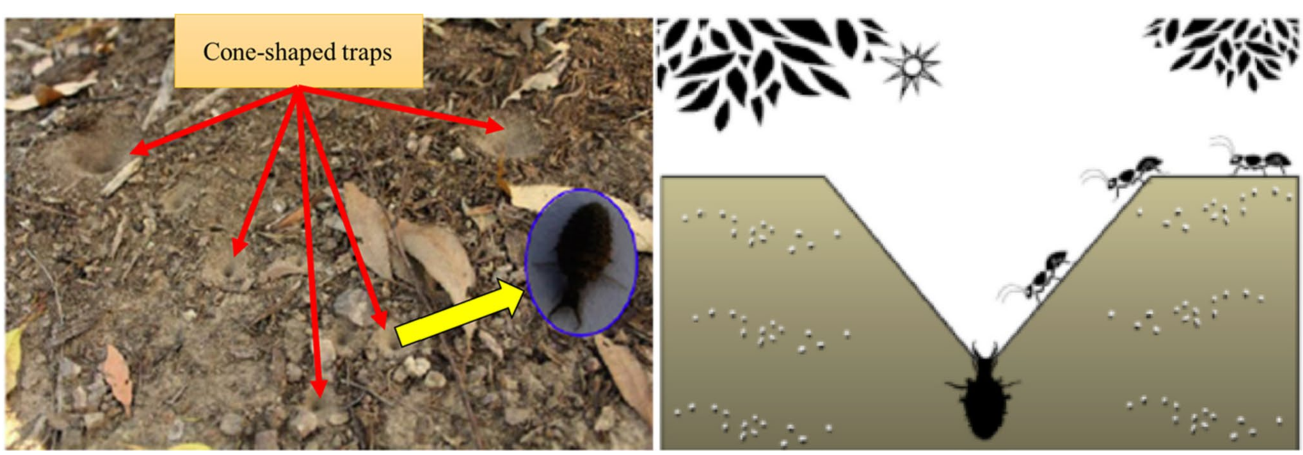
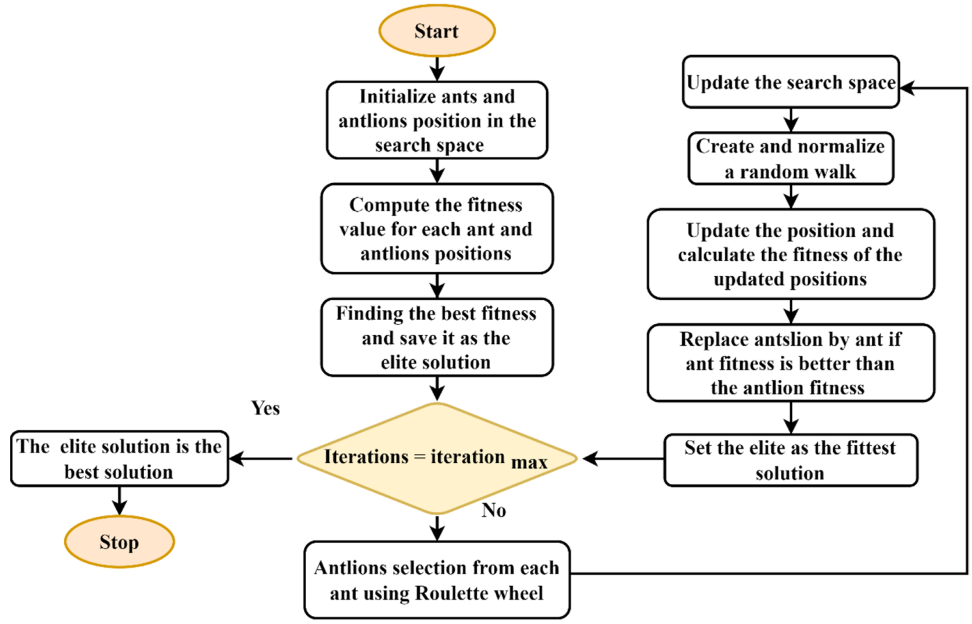


Fig. 8 View of cone-shaped pits and ant hunting by antlion (Mirjalili 2015a; Lawal et al. 2021c)

Fig. 9 Flowchart of antlion optimizer



immediately and try to get away the trap. One of the interesting steps in hunting is that, the antlions intelligently throw the sand to the edge of the pit so that the prey slides to the bottom of the pit. After the prey gets caught in the jaw, the ant pulls it underground and consumes it. Finally, they start repairing the pit for the next hunt (Mirjalili 2015b; Lawal et al. 2021a). The general ALO trend shown in Figure 9; as well as, additional explanations are described in the literature (Mirjalili 2015a; Sam'on et al. 2017; Chen et al. 2020; Lawal et al. 2021b).

Multi-Verse Optimizer (MVO)

MVO is a meta-heuristic and population-based algorithm introduced by Mirjalili et al. 2016. Multi-Verse theory is based on the belief that the universe was built on the basis of several large explosions. This theory suggests the existence of several parallel worlds that continue in parallel. The MVO is based on three main contents called white hole, black hole and wormhole (Mirjalili et al. 2016). The multiverse theory's circular model argues that the Big Bang created white holes where parallel worlds collide. Black holes that are completely observed in the universe and behave in contrast to white holes. They absorb each thing, such as light rays, with very high gravitational forces. Different parts of a world are connected by wormholes. Wormholes in multiverse theory act like time and space travel tunnels in which objects are able to move instantly between any corner of a world. An overview of multi-world theory is shown in Figure 10 (Mirjalili et al. 2016).

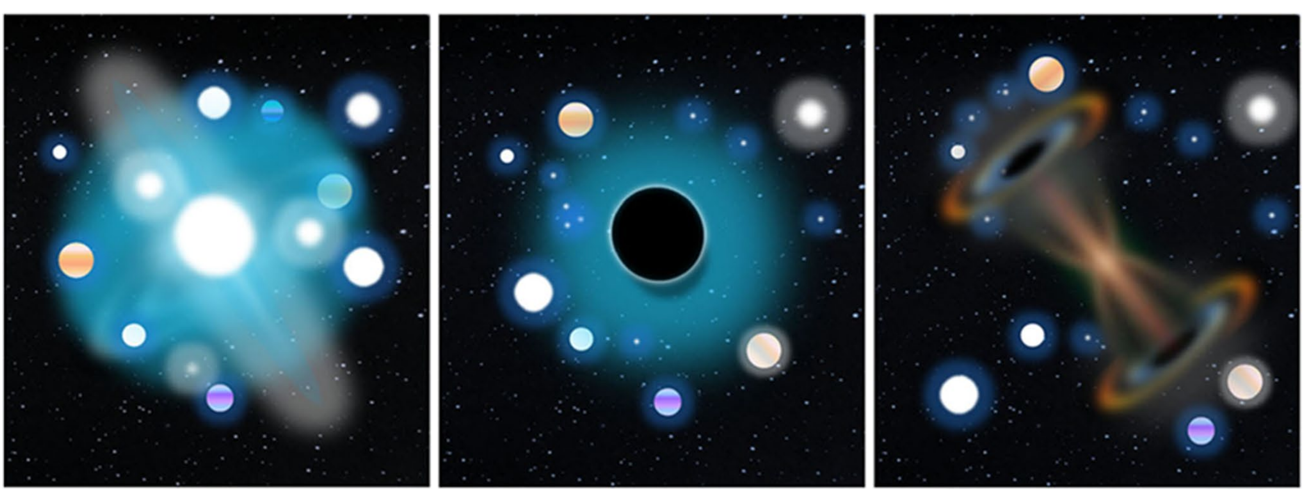


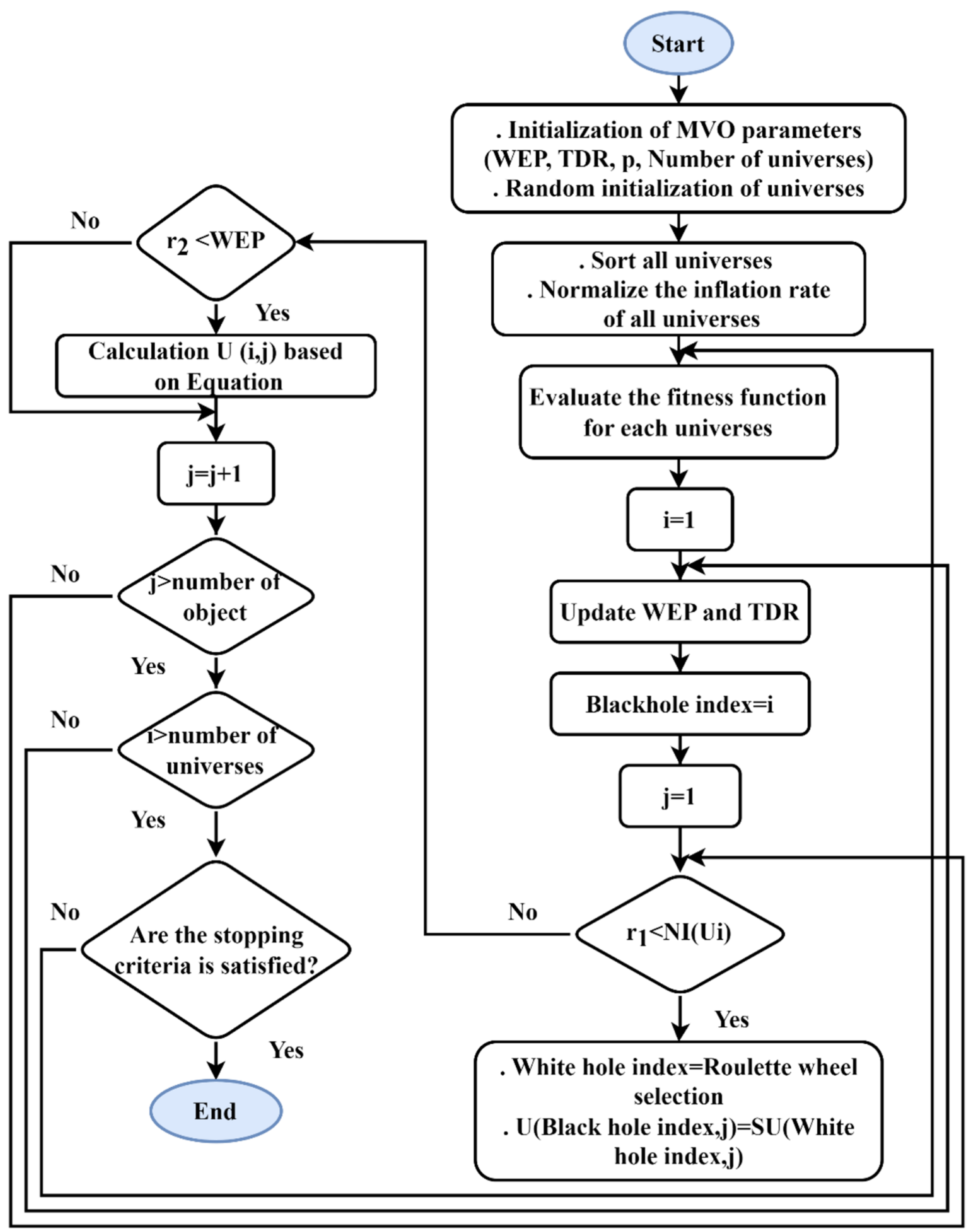
Fig. 10 An overview of multi-world theory (Mirjalili et al. 2016)

The exploration phase and the exploitation phase are the search process by a population-based algorithm. In this algorithm, the concepts of white hole and black hole are used to discover search spaces and the concept of wormhole is used in exploiting search spaces. Suppose that every solution is represented by a world and that every variable in every world is an object in it. Furthermore, any solution or solution is assigned an inflation rate, that's proportional to the performance worth of the solution-related fit function. As well as, we use the term time rather than repetition in this algorithm because it's a general term in multiverse theory (Mirjalili et al. 2016). The general ALO trend shown in Figure 11. In Mirjalili et al. (2016), a detailed description of the MVO can be found.

Study area description and data collection

In Iran, the Sungun copper mine is located 73 km northwest of Ahar, East Azerbaijan Province (see Figure 12). The mine is surrounded by a mountain range approximately 2390 meters high, called Qarabagh. The main products of this mine are copper and molybdenum. According to studies, the total reserves of the mine are estimated at about one billion tons and its definitive reserves are estimated at 388 million tons, with a copper grade of 0.67%. The type of extraction operation in this mine is open, which includes benches with height and slope of 12.5 meters and 63 degrees, respectively.

Fig. 11 Flowchart of multi-verse optimizer algorithm



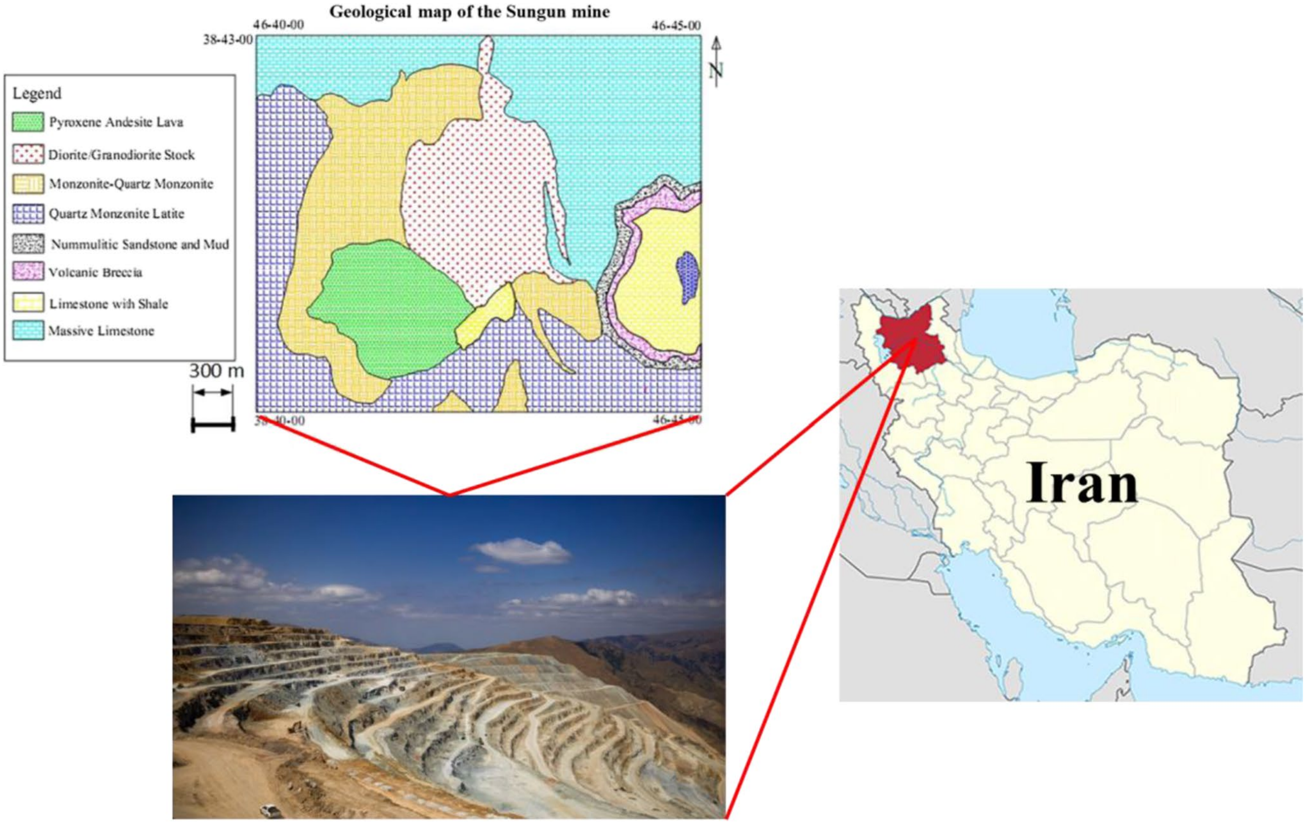


Fig. 12 A view of the location and geology of Sungun copper mine in Iran

Explosion operation data has been recorded and collected. The amount of fly rock resulting from each explosion has been recorded and measured as an output parameter in the mine explosion. Finally, after removing the throw data, 306 data sets were used in this article. Blast-induced flying fragments having an approximate diameter of 10 cm, or more, were considered as flyrock as such flying fragments may cause fatal injuries or damage (Trivedi et al. 2016). In the mine, a total station and a handheld GPS were used to record the fly-rock distance from the blast face. Input parameters for blast design include number of blast holes, sub-drilling, length of charge, hole diameter, spacing, average depth of blast holes, load, stemming, powder factor, etc.

Database

In this article, according to the statistical indicators shown in Table 1, a comprehensive database consisting of 306 datasets with an output and fourteen input parameters has been provided, showing the range of input and output parameters as well. In addition, in Figure 13, for the input data in Figure 8, the Pearson correlation can be seen schematically in a matrix. This analysis enables us to examine the relationship between the input variables. Many studies have shown that correlation analysis is a powerful tool to determine the strength of these relationships (Khoshalan et al. 2021; Dehghani 2018). Pearson correlation coefficients were used in this study to quantify the qualitative correlations observed between the input data. Linear correlation is measured by Pearson correlation coefficient and as a result, a value between +1 and -1 is used to indicate the degree of linear dependence between the two variables. The coefficient +1, 0, -1, respectively, indicates the affirmative correlation, no correlation and finally the negative correlation (Pearson 1895; Dehghani 2018). The definition of Pearson cross-correlation coefficient is as follows:

$$r_{i,c} = \frac{\mathrm{cov}\left(P_i, P_c\right)}{\sigma_{Pc} \times \sigma_{Pi}} \tag{3}$$

where $r_{i,c}$ is the Pearson cross-correlation coefficient between parameter i and second input, σ_{Pc} and σ_{Pi} are the standard deviations of the value of first input and value of parameter i, respectively, and the covariance between the first input and value of parameter i is calculated as below:

Table 1 Statistical indicators of parameters

Statistics	Symbol	Mean	Median	Std. Deviation	Variance	Range	Mini	Max	
blasthole Diameter	A	5.03	5.50	0.75	0.56	3.00	3.00	6.00	Input
Depth	B	10.46	11.75	2.99	8.96	12.50	3.00	15.50	
Subdrilling	C	0.25	0.00	0.45	0.20	3.00	0.00	3.00	
No of blastholes	D	35.02	24.00	34.11	1163.42	232.00	3.00	235.00	
Spacing	E	4.77	5.00	0.83	0.69	3.50	2.50	6.00	
Burden	F	3.96	4.00	0.66	0.44	3.00	2.00	5.00	
Total length	G	325.64	250.00	243.36	59225.91	1849.20	4.00	1853.20	
ANFO	H	2166.92	1800.00	1541.94	2377588.81	10610.00	90.00	10700.00	
Dynamite	I	57.08	45.00	45.95	2111.44	302.00	0.00	302.00	
Total rock blasted	J	5301.77	4121.63	3990.11	15920953.47	30701.04	279.92	30980.96	
st	K	3.17	3.20	0.53	0.28	2.40	1.60	4.00	
pf	L	0.42	0.40	0.11	0.01	0.82	0.18	1.00	
SpD	M	0.07	0.06	0.03	0.00	0.23	0.00	0.23	
Length Charge	N	7.29	8.50	2.84	8.06	10.90	1.00	11.90	
Fly rock	FR	69.47	76.00	19.68	387.42	70.00	30.00	100.00	Output

Fig. 13 View of Pearson linear correlation regression for input data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
A	1.00	0.44	0.12	-0.40	0.81	0.75	-0.15	0.26	0.04	0.19	0.75	0.26	-0.80	0.32
B	0.44	1.00	0.58	-0.40	0.36	0.37	0.05	0.29	0.14	0.23	0.37	0.16	-0.44	0.98
C	0.12	0.58	1.00	-0.11	0.11	0.13	0.12	0.23	0.14	0.19	0.13	0.03	-0.18	0.59
D	-0.40	-0.40	-0.11	1.00	-0.39	-0.33	0.83	0.48	0.58	0.53	-0.33	-0.14	0.38	-0.36
E	0.81	0.36	0.11	-0.39	1.00	0.94	-0.19	0.20	0.05	0.25	0.94	-0.23	-0.90	0.21
F	0.75	0.37	0.13	-0.33	0.94	1.00	-0.11	0.23	0.12	0.31	0.95	-0.32	-0.92	0.21
G	-0.15	0.05	0.12	0.83	-0.19	-0.11	1.00	0.82	0.76	0.84	-0.11	-0.07	0.13	0.07
H	0.26	0.29	0.23	0.48	0.20	0.23	0.82	1.00	0.76	0.95	0.23	0.09	-0.24	0.26
I	0.04	0.14	0.14	0.58	0.05	0.12	0.76	0.76	1.00	0.80	0.12	-0.07	-0.07	0.13
J	0.19	0.23	0.19	0.53	0.25	0.31	0.84	0.95	0.80	1.00	0.31	-0.16	-0.27	0.18
K	0.75	0.37	0.13	-0.33	0.94	0.95	-0.11	0.23	0.12	0.31	1.00	-0.32	-0.92	0.21
L	0.26	0.16	0.03	-0.14	-0.23	-0.32	-0.07	0.09	-0.07	-0.16	-0.32	1.00	0.21	0.22
M	-0.80	-0.44	-0.18	0.38	-0.90	-0.92	0.13	-0.24	-0.07	-0.27	-0.92	0.21	1.00	-0.30
N	0.32	0.98	0.59	-0.36	0.21	0.21	0.07	0.26	0.13	0.18	0.21	0.22	-0.30	1.00

Table 2 The formula of the performance measures

Measure	Formula
Variance Accounted For	$VAF = 100\left(1 - \frac{\mathrm{var}(Ximes - Xipred)}{\mathrm{var}(Ximes)}\right)$
R-Squared	$R^2 = 1 - \frac{\sum_{(i=1)}^{N} (\mathrm{Ximes} - \mathrm{Xipred})^2}{\sum_{(i=1)}^{N} \left(\mathrm{Ximes} - \overline{\mathrm{Ximes}}\right)^2}$
Root Mean Square Error	$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\mathrm{Xipred} - \mathrm{Ximes})^2}$
Mean Absolute Error	$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} \lvert \mathrm{Xipred} - \mathrm{Ximes} \rvert$

That: Xipred is the predicted values and Ximes are the measured values.

$$\mathrm{cov}\left(P_i, P_c\right) = \frac{1}{n}\sum_{j=1}^{n}\left(P_{cj} - \overline{P_c}\right)\left(P_{ij} - \overline{P_i}\right) \tag{4}$$

where P_{cj} is the first input j, P_{ij} is the value of second input j, $\overline{P_c}$ is the average of the first input, $\overline{P_{ij}}$ is the average of the value of the second input, and n is the number of datasets (Dehghani 2018; Khoshalan et al. 2021). Figure 8, shows the correlation coefficients between all variables in this study. It is noteworthy that all correlations between predictor variables are statistically significant, with p-value <0.01(Khoshalan et al. 2021).

Moreover, 70% and 30% divisions, which are training and test data, respectively, were selected randomly and used in the present study. This segmentation was performed to find the best statistical relationship between input and output data and the basis of segmentation was random. It should be noted that the above division was considered the same for all intelligent methods and linear regression method.

Results and Discussion

Predicting with linear multivariate regression (LMR)

In this study, evaluation criteria that are most used in engineering were used to compare the performance of models. These indicators include VAF, R^2, RMSE and MAEIdeally, the RMSE and MAE values should be close to zero and the coefficient of determination (R^2) close to 1. As well as, the difference between the variance, which is VAF, should tend to be close to 1 or 100%. (Shakeri et al. 2022b; Khoshalan et al. 2021; Onyelowe et al. 2021a). The four statistical parameters mentioned above were used as criteria for finding the best result for LMR, MFO, GWO, ALO, WOA and MVO intelligent methods (Table 2).

Finally, Equation (5) with values of 0.64, 60.48, 12.51 and 10.05 for R^2, VAF, RMSE and MAE, respectively, were derived to predict flyrock using the LMR method for test and train data.

Table 3 The optimal Models parameters for output (FR)

Parameter	Value
MF0	
NO search agents	240
NO moths (population)	50
Maximum NO iterations	200
GWO	
NO wolves	170
Maximum NO iterations	200
a	Linearly Increased from 2 to 0
WOA	
NO search agents	240
Max NO iterations	200
l	[−1,1]
a	linearly decreased from 5 to 0
b	1
ALO	
NO ants	100
Max NO iterations	200
NO search agents	240
MVO	
NO search agents	240
Max NO iterations	200
*NO: number of	

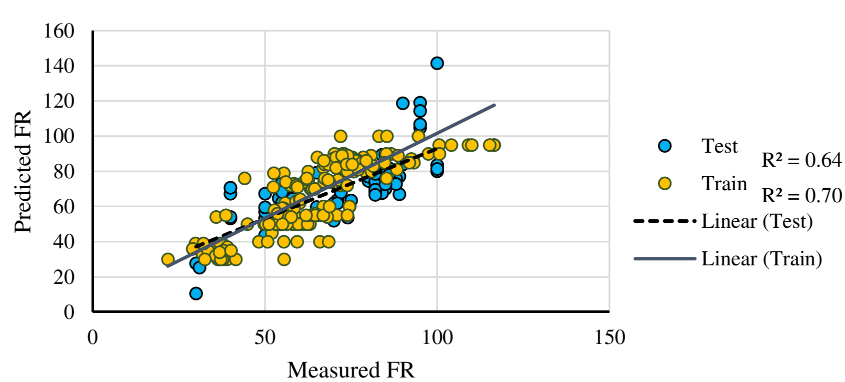


Fig. 14 R-squared value calculated using LMR to predict flyrock

Table 4 Results of all methods for flyrock anticipation

Model	Train				Test			
	R^2	VAF	RMSE	MAE	R^2	VAF	RMSE	MAE
GWO	0.93	92.55	5.33	3.84	0.88	88.35	6.94	4.73
MFO	0.86	85.97	7.35	5.42	0.83	83.06	8.17	6.05
WOA	0.82	82.34	8.22	5.66	0.82	81.88	8.47	6.09
ALO	0.87	86.59	7.16	5.34	0.86	85.58	7.65	5.65
MVO	0.94	93.85	4.85	3.67	0.89	89.39	6.76	4.26
LMR	0.70	69.66	11.11	9.22	0.64	60.48	12.51	10.05

$$\begin{aligned} \mathbf{FR} = & 135.465 + (19.833 \times A) + (6.244 \times C) + (0.117 \times D) \\ & + (-7.667 \times E) + (-31.474 \times F) + (-0.045 \times G) \\ & + (0.011 \times H) + (-0.004 \times I) + (-0.003 \times J) \\ & + (-11.012 \times L) + (-115.285 \times M) + (0.946 \times N) \end{aligned} \tag{5}$$

As well as, figure 14 shows the relationship between the actual and predicted value of FR with linear regression for test data.

Parameter Settings

The experimental settings of the parameters of all the intelligent algorithms used in this study to anticipate the outputs are summarized in Table 3.

The global parameter settings were set to 240 for the number of search agents and 200 for the number of duplicates. These values were selected based on their good performance in previous studies (Chen et al. 2020; Lawal et al. 2021a; Memarzadeh et al. 2020; Louis et al. 2019; Lawal et al. 2021b; Bui et al. 2021).

Heuristic methods results

Artificial intelligence approaches are constantly evolving due to limitations of the laboratory environment. According to recent studies, researchers are convinced that artificial intelligence methods can be used to evaluate parameters more accurately than conventional approaches. As

Fig. 15 R-squared value calculated to predict fly-rock calculated using, **a**) GWO, **b**) MFO, **c**) WOA, **d**) ALO, **e**) MVO

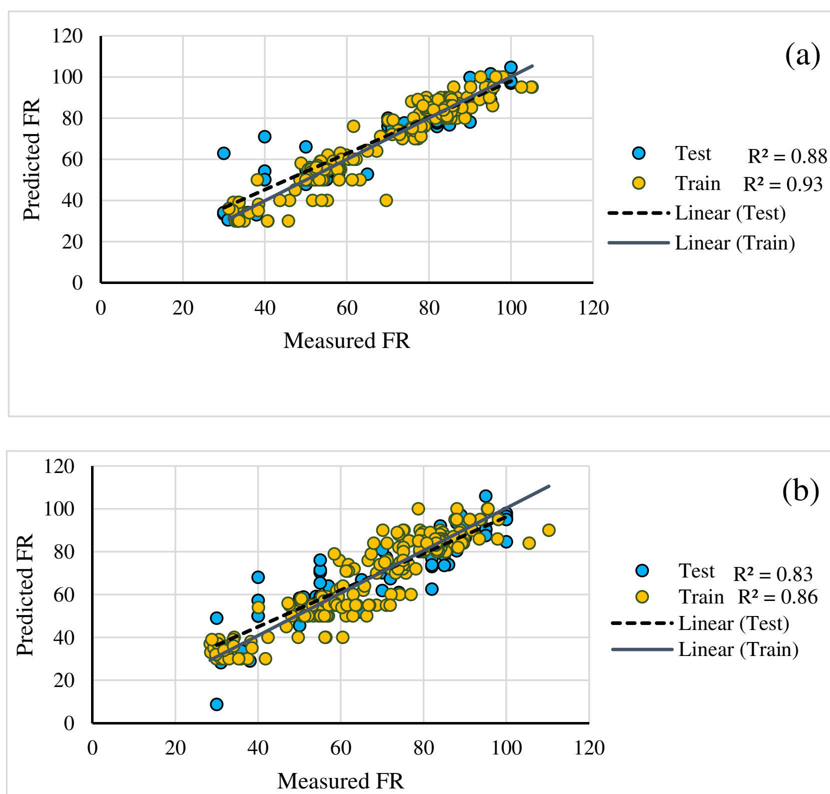
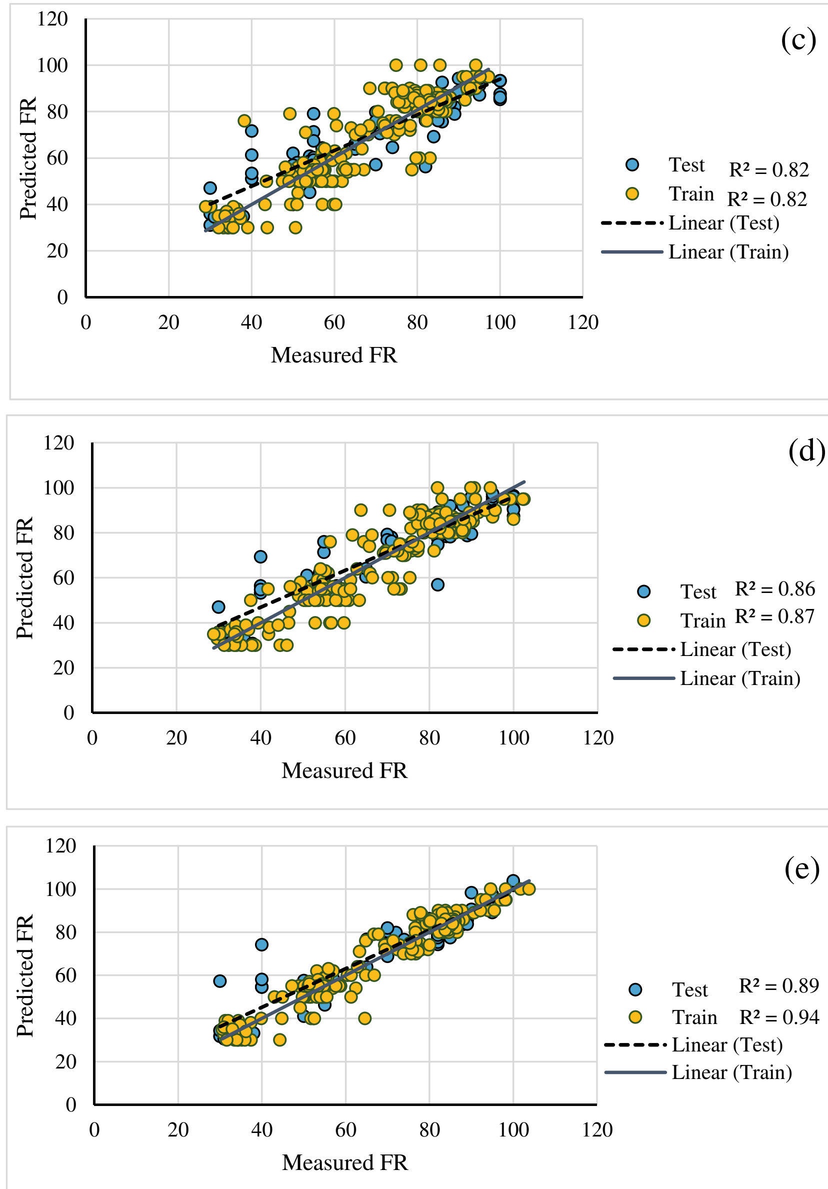


Fig. 15 (continued)



before said, the main purpose of current paper is to predict flyrock (FR) based on the input parameters showed in Table 1.

The value of R^2 calculated by LMR indicated the low accuracy of this method in predicting FR. Therefore, heuristic methods including GWO, MFO, WOA, ALO and MVO were used to predict FR. The results of FR prediction are listed in Table 4 and based on the highest values for R^2, VAF and the lowest values obtained for MAE, RMSE for both training and test data.

Table 4 and figure 15 show that the results of the MVO method in performing flyrock prediction are better than other methods in all criteria. GWO came in second place and then MFO, ALO and WOA in the next ranks for FR prediction, respectively. While LMR results showed that, compared to all five intelligent methods used in this study, it has less accuracy for predicting FR and it is placed in the last rank. Furthermore, the predictive merits of these models were illustrated through the utilization of a Taylor diagram (see Fig. 16). This aforementioned schematic

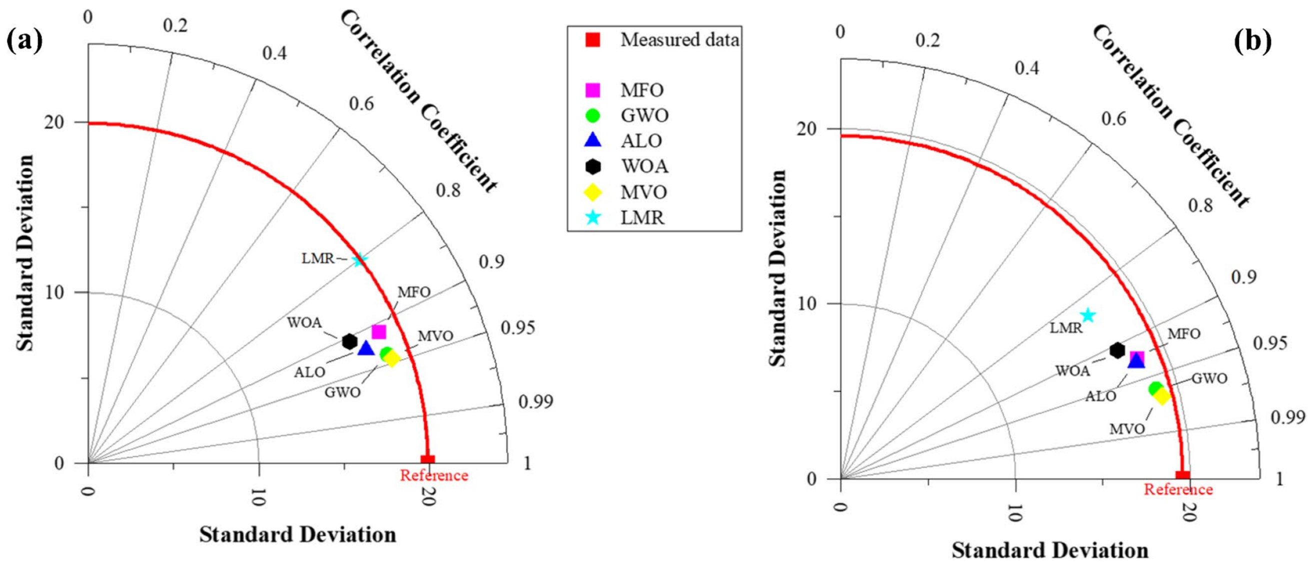


Fig. 16 The assessment of the measured values against the predicted values across all methodologies for **a**) the test data, and **b**) the train data

offers a visual depiction of the projected results for each model in the shape of a spatial curve that exhibits correlation with a predetermined benchmark.

Sensitivity analysis

Sensitivity analysis tries to evaluate the significance of each "cause" (input variable) on the "effect" (output variable). In this work, sensitivity analysis was performed using diagrams called tornadoes and spiders. The purpose of this analysis was to find the most important parameters affecting the flyrock phenomenon. These graphs are typically created by fixing an input distribution to a low value (say its fifth percentile), running a simulation, recording the output means and then repeating the process with a high value (say its 95th percentile) of the input distribution to define extremes of the bars.

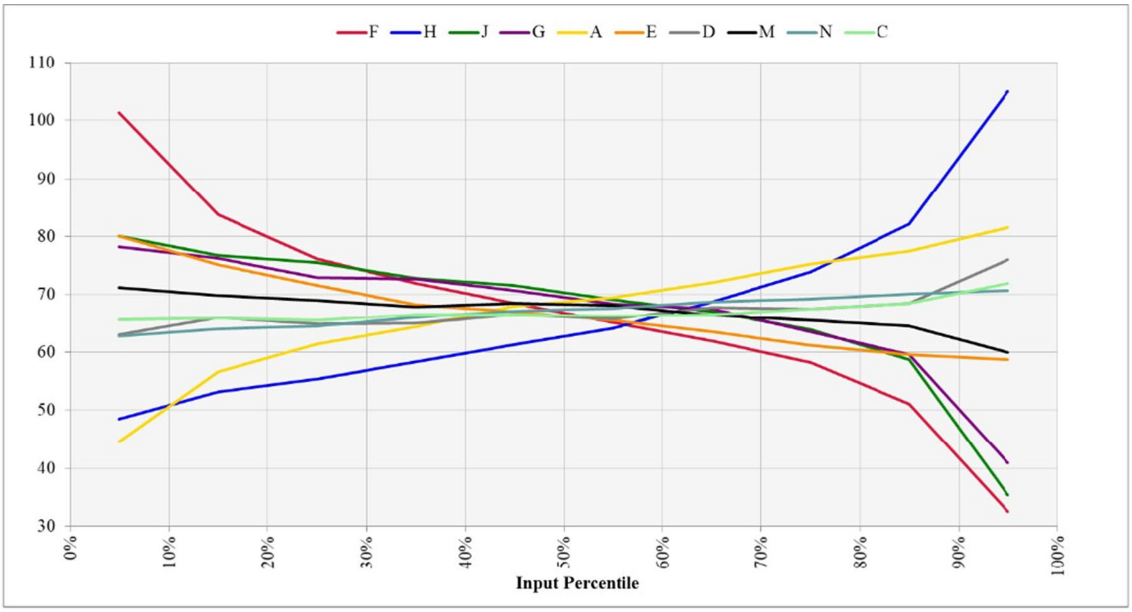
Results from the sensitivity analysis are shown in Figure. 17. This figure shows that the Burden, ANFO, total rock blasted, total length and blast hole diameter are the most significant parameters determining the flyrock, respectively. Besides, dynamite has the least effect on flyrock.

Conclusions

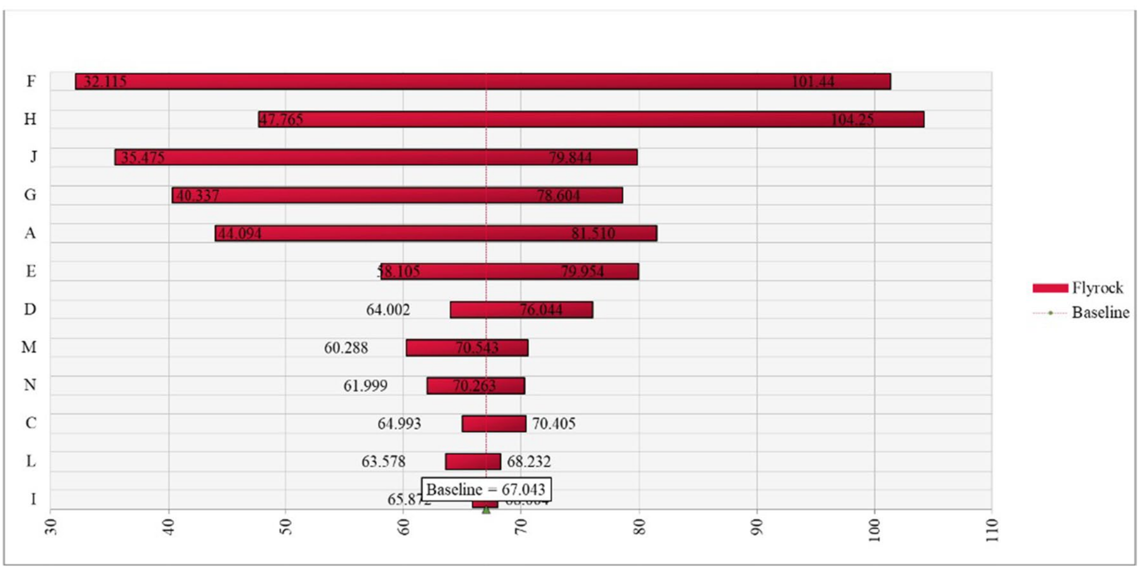
Flyrock is one of the adverse effects that have to be managed in order to minimize the blasting impacts. If its potential damage is not predicted and errors occur during the blasting, it can cause many irreparable problems for surrounding area. Therefore, the prediction of blast-induced flyrock should be considered more carefully to eliminate or minimize the possibility of damage to adjacent structures.

In the present study, different models were used to evaluate and anticipate the flyrock due to the blasting in the Songun mine. linear multivariate regression (LMR) and artificial intelligence algorithm such as Gray Wolf Optimization Algorithm (GWO), Moth-Flame Optimization Algorithm (MFO), Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO) and Multi-Verse Optimizer (MVO) were built to predict fly-rock in 306 blast operations in the case study. The efficiency of these methods was compared based on statistical criteria including R^2, VAF, RMSE and MAE. As a result, the worthies of these parameters for the obtained MVO were 0.89, 89.39%, 6.76 and 4.26 for test data, respectively. Therefore, the MVO technique was considered the best model for predicting fly-rock distance. Results also showed that all intelligent methods have a relatively high ability to predict fly rock compared to the LMR method.

In addition, the sensitivity analysis results shows that the Burden, ANFO, total rock blasted, total length and blast hole diameter are the most significant parameters determining the flyrock, respectively. Besides, dynamite has the least effect on flyrock.



(a)



(b)

Fig. 17 Sensitivity analysis, **a**) Spider graph; **b**) Tornado graph

Funding There are no funding sources.

Data availability The datasets will be provided on request.

Declarations

Conflict of interest There are no conflicts of interest.

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